Study Of Gaussian & Impulsive Noise Suppression Schemes In Images

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Certificate

This is to certify that the work in the thesis entitled *Study Of Gaussian & Impulsive Noise Suppression Schemes In Images* by *Ravi Karan Sharma & Rohit Nibariya* is a record of an original research work carried out by them under my supervision and guidance in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology in Computer Science and Engineering during the session 2005–2009 in the department of Computer Science and Engineering, National Institute of Technology Rourkela. Neither this thesis nor any part of it has been submitted for any degree or academic award elsewhere.

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Abstract

Noise is introduced into images usually while transferring and acquiring them. The main type of noise added while image acquisition is called Gaussian noise while Impulsive noise is generally introduced while transmitting image data over an unsecure communication channel , while it can also be added by acquiring. Gaussian noise is a set of values taken from a zero mean Gaussian distribution which are added to each pixel value. Impulsive noise involves changing a part of the pixel values with random ones.

Various techniques are employed for the removal of these types of noise based on the properties of their respective noise models. Impulse Noise removal algorithms popularly use ordered statistics based filters. The first one is an adaptive filter using center-weighted median. In this method, the difference of the center weighted mean of a neighborhood with the central pixel under consideration is compared with a set of thresholds.

Another method which takes into account the presence of the noise free pixels has been implemented.It convolutes the median of each neighborhood with a set of convolution kernels which are oriented according to all possible configurations of edges that contain the central pixel,if it lies on an edge.

A third method which deals with the detection of noisy pixels on the binary slices of an image is implemented. It is based on threshold Boolean filtering. The filter inverts the value of the central pixel if the number of pixels with values opposite to it is more than the threshold.

The fourth method has an efficient double derivative detector, which gives a decision based on the value of the double derivative. The substitution is done with the average gray scale value of the neighborhood.

Gaussian Noise removal algorithms ideally should smooth the distinct parts of the image without blurring the edges.A universal noise removing scheme is implemented which weighs each pixel with respect to its neighborhood and deals with Gaussian and impulse noise pixels differently based on parameter values for spatial, radiometric

and impulsive weight of the central pixel.

The aforementioned techniques are implemented and their results are compared subjectively as well as objectively.

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Chapter 1

Introduction

1.1 Image Processing

Vision is a complicated process that requires numerous components of the human eye and brain to work together.The sense of vision has been one of the most vital senses for human survival and evolution. Humans use the visual system to see or acquire visual information, perceive, i .e. process and understand it and then deduce inferences from the perceived information. The field of image processing focuses on automating the process of gathering and processing visual information. The process of receiving and analyzing visual information by digital computer is called *digital image processing.*

An image may be described as a two-dimensional function I.

$$I = f(x, y) \tag{1.1}$$

where x and y are spatial coordinates. Amplitude of f at any pair of coordinates (x, y) is called intensity I or gray value of the image. When spatial coordinates and amplitude values are all finite, discrete quantities, the image is called digital image [1].

Digital image processing may be classified into various subbranches based on methods whose: [1]

- input and output are images and
- inputs may be images where as outputs are attributes extracted from those images.

Following is the list of different image processing functions based on the above two classes.

- Image Acquisition
- Image Enhancement
- Image Restoration
- Color Image Processing
- Multi-resolution Processing
- Compression
- Morphological Processing
- Segmentation
- Representation and Description
- Object Recognition

For the first seven functions the inputs and outputs are images where as for the rest three the outputs are attributes from the input images. With the exception of image acquisition and display most image processing functions are implemented in software. Image processing is characterized by specific solutions, hence the technique that works well in one area can be inadequate in another. The actual solution of a specific problem still requires a significant research and development [2].

Out of the ten sub-branches of digital image processing, cited above, this thesis deals with image restoration. In thesis various restoration methodology are used and various inputs are restored using these methods.

This is chapter is organized as follows. Document Image Processing is discussed in Section 1.2. The problem definition is described in Section 1.3. Motivation behind carrying out the work is stated in Section 1.4. Organization of the thesis is outlined in Section 1.5.

1.2 Noise In Image Processing

Image noise is a random, usually unwanted, variation in brightness or color information in an image. Image noise can originate in film grain, or in electronic noise in the input device (scanner or digital camera) sensor and circuitry, or in the unavoidable shot noise of an ideal photon detector. Image noise is most apparent in image regions with low signal level, such as shadow regions or underexposed images. High levels of noise are almost always undesirable, but there are cases when lower levels of noise may be useful, for example to prevent discretization artifacts (color banding or posterization). Noise purposely added for such purposes is called dither.

Salt-and-pepper noise

Fat-tail distributed or "impulsive" noise is sometimes called salt-and-pepper noise or spike noise. An image containing salt-and-pepper noise will have dark pixels in bright regions and bright pixels in dark regions. This type of noise can be caused by dead pixels, analog-to-digital converter errors, bit errors in transmission, etc. [1]

Shot noise

The dominant noise in the lighter parts of an image from an image sensor is typically that caused by statistical quantum fluctuations, that is, variation in the number of photons sensed at a given exposure level; this noise is known as photon shot noise. [3] Shot noise has a root-mean-square value proportional to the square root of the image intensity, and the noises at different pixels are independent of one another. Shot noise follows a Poisson distribution, which is usually not very different from Gaussian. In addition to photon shot noise, there can be additional shot noise from the dark leakage current in the image sensor; this noise is sometimes known as "dark shot noise" [3] or "dark-current shot noise". [4] Dark current is greatest at "hot pixels" within the image sensor; the variable dark charge of normal and hot pixels can be subtracted off (using "dark frame subtraction"), leaving only the shot noise, or random component, of the leakage;if dark-frame subtraction is not done, or if the exposure time is long enough that the hot pixel charge exceeds the linear charge capacity, the noise will be more than just shot noise, and hot pixels appear as salt-and-pepper noise.

Amplifier noise (Gaussian noise)

The standard model of amplifier noise is additive, Gaussian, independent at each pixel and independent of the signal intensity, caused primarily by JohnsonNyquist noise (thermal noise), including that which comes from the reset noise of capacitors ("kTC noise").In color cameras where more amplification is used in the blue color channel than in the green or red channel, there can be more noise in the blue channel. [3] Amplifier noise is a major part of the "read noise" of an image sensor, that is, of the constant noise level in dark areas of the image.[9]

Quantization noise (uniform noise)

The noise caused by quantizing the pixels of a sensed image to a number of discrete levels is known as quantization noise; it has an approximately uniform distribution, and can be signal dependent, though it will be signal independent if other noise sources are big enough to cause dithering, or if dithering is explicitly applied.

Film grain

The grain of photographic film is a signal-dependent noise, related to shot noise.That is, if film grains are uniformly distributed (equal number per area), and if each grain has an equal and independent probability of developing to a dark silver grain after absorbing photons, then the number of such dark grains in an area will be random with a binomial distribution; in areas where the probability is low, this distribution will be close to the classic Poisson distribution of shot noise; nevertheless a simple Gaussian distribution is often used as an accurate enough model. Film grain is usually regarded as a nearly isotropic (non-oriented) noise source, and is made worse by the distribution of silver halide grains in the film also being random.

Non-isotropic noise

Some noise sources show up with a significant orientation in images. For example, image sensors are sometimes subject to row noise or column noise.In film, scratches are an example of non-isotropic noise.

Image noise reduction

Noise cannot be removed without the loss of some information in the form of image detail. Nevertheless, noise-reduction algorithms have been developed to reduce noise without degrading image information too much.

1.3 Problem Definition

During image acquisition and transmission, noise is inevitably introduced into images. Gaussian noise removal algorithms ideally should be as accurate as possible to detect edges in the image. Impulse noise removal algorithms are rank ordered statistic filters, which depend on the pixel values of the neighborhood to correct the noisy pixel. Noise removal is essential to obtain workable images.

Two types of impulsive noise models are described below. Let $Y_{i,j}$ be the gray level of an original image Y at pixel location (i, j) and $[n_{min}, n_{max}]$ be the dynamic range of Y. Let Xi,j be the gray level of the noisy image X at pixel (i, j) location. Impulsive Noise may then be defined

$$X_{ij} = \begin{cases} Y_{i,j}, with\ 1-p \\ R_{ij}, with\ p \end{cases} \tag{1.2}$$

where,$R_{i,j}$ is the substitute for the original gray scale value at the pixel location (i, j). When $R_{i,j}$ [nmin, nmax], the image is said to be corrupted with Random Valued Impulsive Noise (RVIN) and when $R_{i,j} \in [n_{min}, n_{max}]$, it known as Fixed Valued Impulsive Noise or Salt & Pepper Noise (SPN).

1.4 Motivation

Impulse noise removal consists of detecting the noisy pixel taking into account the edges and substituting the noisy pixel with the best approximation of the correct pixel value based on the neighborhood. Gaussian noise removal consists of detecting the edges, preserve them for blurring and smoothen the locally smooth and distinct areas. Finding the most complete and sound noise filter is the primary motivation behind this work.

1.5 Thesis Organisation

The rest of the thesis is organized as follows:

Chapter 2 various impulse noise removal algorithms are implemented . The first one is an adaptive filter using center-weighted median. Second method which takes into account the presence of the noise free pixels has been implemented. It convolutes the median of each neighborhood with a set of convolution kernels which are oriented according to all possible configurations of edges. A third method which deals with the detection of noisy pixels on the binary slices of an image is implemented. It is based on threshold Boolean filtering. The fourth method has an efficient double derivative detector, which gives a decision based on the value of the double derivative.

Chapter 3 deals with gaussian noise removal algorithms.A universal noise removing scheme is implemented which weighs each pixel with respect to its neighborhood and deals with Gaussian and impulse noise pixels differently based on parameter values for spatial, radiometric and impulsive weight of the central pixel.

Finally **Chapter 4** presents the concluding remarks,comparisons and results with scope for further research work.

Chapter 2

Impulsive Noise Models

There are various methods to detect and suppress noise in an image.Here we have implemented various algorithms mainly focussing on impulsive noise and compared the results based on our implementation.

2.1 A New Impulse Detector for Switching Median Filters

An impulsive noise detection technique for switching median filters is presented [5] , which is based on the minimum absolute value of four convolutions obtained using one-dimensional Laplacian operators.In particular, the proposed filter is directed toward improved line preservation.

2.1.1 Algorithm

1. Let X_{ij} and Y_{ij} represent the pixel values at position (i,j) in the corrupted and restored images, respectively. The standard median filter outputs the median value of the samples in the (2N+1) * (2N+1) window centered at X_{ij} ,

$$M_{ij} = median\{X_{i-N,j-N}, ..., X_{ij}, ..., X_{i+N,j+N}\} \tag{2.1}$$

2. The median-based impulse detector measures $\|X_{ij} - M_{ij}\|$ and compares it with a predefined threshold

$$\alpha_{ij} = \begin{cases} 1, \|X_{ij} - M_{ij}\| > T_1 \\ 0, \|X_{ij} - M_{ij}\| \leq T_1 \end{cases} \tag{2.2}$$

$$Y_{ij} = \{\alpha_{ij}.M_{ij} + (1 - \alpha_{ij}).X_{ij}\} \tag{2.3}$$

3. The input image is first convolved with a set of convolution kernels.

4. The minimum absolute value of these four convolutions (denoted as R_{ij}) is used for impulse detection, which can be represented as

$$R_{ij} = min\{\|X_{ij} \oplus K_p\| : p = 1 \ to \ 4|\} \tag{2.4}$$

where k_p is the pth kernel, and $\oplus$ denotes a convolution operation.

5. The value of r_{ij} detects ipulses due t the following reasons
•R_{ij} is large when the current pixel is an isolated impulse.
•R_{ij} is small when the current pixel is noise-free flat-region pixel.
•R_{ij} is small when the current pixel is an edge pixel.

6. Then all the convolution values are sorted out.

7. Take the lowest convolution value and compare it with a threshold, taken as 100.

$$\alpha_{ij} = \begin{cases} \{1, R_{ij} > T|\} \\ \{0, R_{ij} \leq T|\} \end{cases} \tag{2.5}$$

2.2 Adaptive Impulse Detection Using Center-Weighted Median Filters

A impulse noise detection technique for median-based impulse detection strategies tend to work well for fixed-valued impulses but poorly for random valued impulse noise, or vice versa. A novel adaptive operator, which forms estimates based on

(a) First image with 5 % noise

(b) Corrected image of (a)

(c) First image with 10 % noise

(d) Corrected image of (c)

Figure 2.1: Image with noise and corrected image using a Impulse Detector for Switching Median Filters

the differences between the current pixel and the outputs of center-weighted median (CWM) filters with varied center weights is taken [6].

2.2.1 Algorithm

1. Weight adjustment is applied to original sample X_{ij} within sliding window , can be described as

$$Y_{ij}^{w} = median(X_{ij}) \tag{2.6}$$

where

(a) First image with 15 % noise

(b) Corrected image of (a)

(c) First image with 20 % noise

(d) Corrected image of (c)

Figure 2.2: Image with noise and corrected image using a Impulse Detector for Switching Median Filters

$$X_{ij} = \{X_{i-s,j-t}\ ,\ w\diamond X_{ij}\ \|(s,t) \in W, (s,t) \neq (0,0)\} \tag{2.7}$$

w=2k+1 and $\diamond$ represents the repetition operation.

For each (2N+1)*(2N+1) size neighborhood , take a weighted median of the central pixel. Weight increases in increments of 1 in each iteration.

The decision making mechanism is realized by employing a set of thresholds T_k (k = 0,1,....,L-1) , where $T_{k-1} > T_k$ for (k=1,....,L-1).

2. Take the difference of the median with the central pixel value , we define differences

$$d_k = |Y_{ij}^{w} - X_{ij}| = |Y_{ij}^{(2k+1)} - X_{ij}| \tag{2.8}$$

3. Subtract all pixel values in the neighborhood with the median value. We call this as MAD (Absolute Deviations from the Median), and take their median

$$MAD = median|X_{i-s,j-t} - Y_{ij}^{1}||(s,t) \in W \tag{2.9}$$

4. Calculate the value of the threshold as:

   $T_k = s.MAD + \delta_k.$

5. The main filter formula is

$$\hat{X}_{ij} = \begin{cases} Y_{ij}^{1}, ifE\ k,\ d_k > T_k \\ X_{ij},\ otherwise \end{cases} \tag{2.10}$$

6. The determination of the thresholds is simplified to the adjustment of parameter s.

2.3 Impulsive Noise Removal Using Threshold Boolean Filtering Based on the Impulse Detecting Functions

A filter for impulsive noise removal is presented here. The problem of impulsive noise elimination is closely connected with the problem of maximal preservation of image edges. To avoid smoothing of the image during filtering, all noisy pixels must be detected. We consider here an approach, which is based on threshold Boolean filtering, where the binary slices of an image, obtained by the threshold decomposition, are processed by the impulse-detecting Boolean functions.

(a) First image with 5 % noise

(b) Corrected image of (a)

(c) Second image with 10 % noise

(d) Corrected image of (c)

Figure 2.3: Image with Noise and with corrected images using Adaptive Impulse Detection Using Center-Weighted Median Filters

2.3.1 Algorithm

An attractive way to implement noise elimination is by splitting an image into binary slices, with further processing of these slices as binary images and merging the processing results into the resulting image.Filtering of binary images itself is reduced to their processing using some Boolean function [7].

1. The following Boolean function was proposed to detect and remove impulses from binary images in:

(a) First image with 15 % noise

(b) Corrected image of (a)

(c) First image with 20 % noise

(d) Corrected image of (c)

Figure 2.4: Image with noise and corrected image using Adaptive Impulse Detection Using Center-Weighted Median Filters

$$Y\begin{vmatrix} x_1 & x_2 & x_3 \\ x_4 & x_5 & x_6 \\ x_7 & x_8 & x_9 \end{vmatrix} = \begin{cases} \bar{x}_5, & \text{if } \|x_i|\overline{x_i} = x_5\| \geq 5 \\ x_5, & \text{otherwise} \end{cases} \tag{2.11}$$

2. Compare the value of the windows central element x_5 to other signal values from the same window , the value of the central element eventually is replaced by the median.

3. The procedure is equivalent to stack filtering , the value of the central element eventually is replaced by the median and a threshold parameter is used. The corresponding Boolean function is defined as follows :

$$f\begin{vmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \\ x_8 \\ x_9 \end{vmatrix} == [x_5 \wedge (\wedge_{j=1}^{T}(\vee_{k=i_{j1}}^{i_{jt}} x_k))] \vee [\overline{x_5} \wedge (\vee_{j=1}^{T}(\wedge_{k=i_{j1}}^{i_{ji}} x_k))] \tag{2.12}$$

4. $\wedge$ and $\vee$ are the signs of conjunction and disjunction, respectively. The function inverts the value of the central pixel of a 3X3 window, if the number of pixels with values opposite to , exceeds and preserves it otherwise.

5. We obtain a function of 25 variables. In order to do it, 3X3 and 5X5 levels around the central pixel should be considered separately, because this allows for more careful noise detection.

6. If consider a natural generalization of the function f for a 5X5 window , as follows:

$$f_{5X5}\begin{vmatrix} x_1 & x_2 & x_3 & x_4 & x_5 \\ x_6 & x_7 & x_8 & x_9 & x_{10} \\ x_{11} & x_{12} & x_{13} & x_{14} & x_{15} \\ x_{16} & x_{17} & x_{18} & x_{19} & x_{20} \\ x_{21} & x_{22} & x_{23} & x_{24} & x_{25} \end{vmatrix} = [x_{13} \wedge (\wedge_{j=1}^{T}(\vee_{k=i_{j1}}^{i_{jt}} x_k))] \vee [\overline{x_{13}} \wedge (\vee_{j=1}^{T}(\wedge_{k=i_{j1}}^{i_{jt}} x_k))] \tag{2.13}$$

Here t is a threshold.It is the number of all possible elementary conjunctions of variables out of 24.

Let $x^{(k)}(i,j)$ be kth binary slice obtained by the following threshold decomposition of the M+1 - valued signal :

$$x^{(k)}(i,j) = \begin{cases} 1 \ , if \ x(i,j) \geq k \\ 0, \ otherwise. \end{cases} \tag{2.14}$$

7. To continue with threshold Boolean filtering, we need to process the obtained binary slices by one of the Boolean functions Then these binary images, obtained as the processing results, are integrated back into a grayscale image

$$y(i,j) = \sum_{i=0}^{M} F(X_{ij}^{k}) \tag{2.15}$$

where (i,j) are the coordinates of the processed pixel.

8. The values of t and s can be fixed and then the filter can be applied iteratively. Iterative processing can make filtering more accurate.

2.4 Efficient Filtering Of Image Data Corrupted by Impulse Noise

A method for filtering images corrupted with impulse noise ,based on combined impulse detection and selective filtering technique.The impulse detector is a double derivative detector , which gives a decision depending on the magnitude of double derivative [8].The reconstruction of of filter substitutes the corrupted pixel by the average gray scale of it's immediate healthy surroundings.

2.4.1 Algorithm

1. Impulse noise is taken as n_i

$$x_i = y_i + n_i \begin{cases} y_i + A_i, with\ probability,\ p \\ y - i, otherwise \end{cases} \tag{2.16}$$

2. A 3x5 moving window is employed for each picel in the image with test pixel being the center pixel x_{23}.

(a) First image with 5 % noise

(b) Corrected image of (a)

(c) Second image with 10 % noise

(d) Corrected image of (c)

Figure 2.5: Image with Noise and with corrected images using Impulsive Noise Removal Using Threshold Boolean Filtering Based on the Impulse Detecting Functions

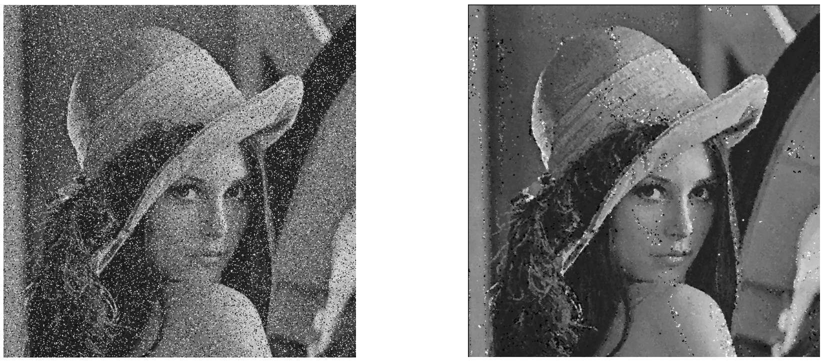
3. The moving window x moves over the entire image and detect presemce of an impulse using the double derivative method.

$$D_c^2 = \begin{vmatrix} D_{c11}^2 & D_{c12}^2 & D_{c13}^2 \\ D_{c21}^2 & D_{c22}^2 & D_{c23}^2 \\ D_{c31}^2 & D_{c32}^2 & D_{c33}^2 \end{vmatrix} \tag{2.17}$$

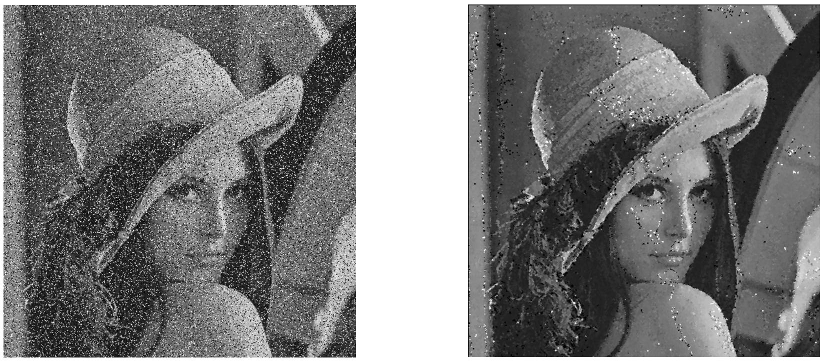
where$D_{cij}^2 = D_{ci(j+1)}^2 - D_{cij}^2 \; D_{cij}^2 = x_{i,(j+1)} - x_{i,j}$

4. The decision on detection of impulse is based on $[Abs(D_c^2) - t]$. If it's value is positive then impulse is detected oterwise not.

5. If impulses appear continously in a row, in such case absolute value of row wise



(a) First image with 15 % noise (b) Corrected image of (a)



(c) Second image with 20 % noise (d) Corrected image of (c)

Figure 2.6: Image with Noise and with corrected images using Impulsive Noise Removal Using Threshold Boolean Filtering Based on the Impulse Detecting Functions

double dreivative with the threshold , t, and filtering it after the column wise double derivative and subsequent filtering is carried out.

6. A 3x3 matrix, f is obtained which is hard limited (H_L) output of $[Abs((D_c^2) - t)]$

$$f = H_L[Abs((D_c^2) - t)]where(H_L(x)) = \begin{cases} 0, ifx \geq 0 \\ 1, otherwise \end{cases} \tag{2.18}$$

7. The gray scale value, s to be substituted at the erroneous pixel's placeis given by:

$$s = \frac{1}{n}\sum_{i=1}^{3}\sum_{j=1}^{3} f_{i,j}\, x_{i,j+1} \tag{2.19}$$

Here n is the number of healthy pixels in the immeadiate surrounding of the test pixel, which is found out by counting the number of ones in the f matrix.

(a) First image with 5 % noise (b) Corrected image of (a)

(c) Second image with 10 % noise (d) Corrected image of (c)

Figure 2.7: Imaged with Noise and with corrected images using Efficient Filtering Of Image Data Corrupted by Impulse noise

(a) First image with 15 % noise

(b) Corrected image of (a)

(c) Second image with 20 % noise

(d) Corrected image of (c)

Figure 2.8: Imaged with Noise and with corrected images using Efficient Filtering Of Image Data Corrupted by Impulse noise

Chapter 3

Gaussian Noise Models

Two noise models can adequately represent most noise added to images: additive Gaussian noise and Impulsive noise.Additive Gaussian noise is characterized by adding to each image pixel a value from a zero-mean Gaussian distribution.Such noise is usually introduced during image acquisition. The zero-mean property of the distribution allows such noise to be removed by locally averaging pixel values. Ideally, removing Gaussian noise would involve smoothing inside the distinct regions of an image without degrading the sharpness of their edges.

3.1 A Universal Noise Removal Algorithm With an Impulse Detector

A local image statistic for identifying noise pixels in images corrupted with impulse noise of random values is introduced. The statistical values quantify how different in intensity the particular pixels are from their most similar neighbours.This statistic may be incorporated into a filter designed to remove additive Gaussian noise [9]. The result is a new filter capable of reducing both Gaussian and impulse noises from noisy images effectively.The approach is extended to automatically remove any mix of Gaussian and impulse noise.

3.1.1 Algorithm

1. Let x = (x_1 , x_2) be the location of the pixel under consideration, and let

$$\Omega_x := x + (i, j) : -N \leq i, j \leq N \tag{3.1}$$

be a set of points in (2N+1)*(2N+1) neighborhood centered at x for some positive integer N.

$$\Omega_x^0 = \Omega_x(1)\ x \tag{3.2}$$

2. Define d_{xy} as the absolute difference in the intensity of the pixels between x and y

$d_{x,y} = |u_x - u_y|$

3. Sort the $d_{x,y}$ values in increasing order and define

$$ROAD_m(x) = \sum_{i=1}^{m} r_i(x) \tag{3.3}$$

Calculate the road value of the central pixel in its neighborhood (m = 4).

4. Calculate the spatial and radiometric weight of each pixel Let x be the location of the pixel under consideration , and let

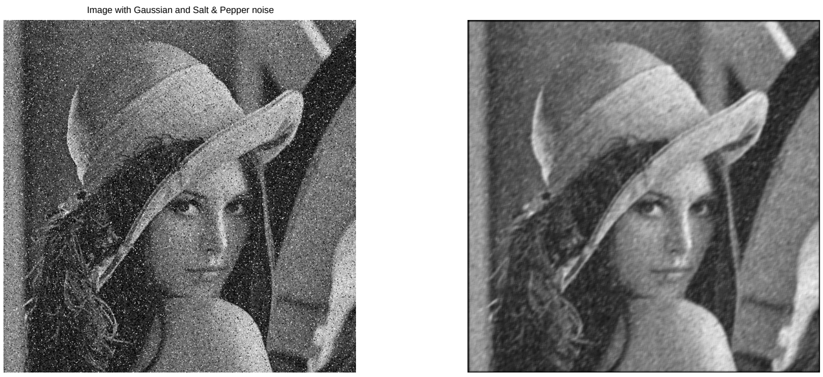
$\Omega = \Omega_x(N)$

be the pixels in (2N+1)*(2N+1) neighborhood of x. The weight of each y $\in$ $\Omega$with respect to x is the product of two components, one spatial and one radiometric

$$w_{x,y} = w_S(x, y) w_R(x, y) \tag{3.4}$$

where

$$w_S(x, y) = e^{(-\frac{|x-y|^2}{2^2_S})} \tag{3.5}$$



(a) First image with mixed noise with variance = 0.01 and impulse probability = 0.05

(b) Corrected image of (a)

Figure 3.1: Image with Mixed noise and corrected image using a A Universal Noise Removal Algorithm With an Impulse Detector

and

$$w_R(x, y) = e^{(-\frac{|u_x - u_y|^2}{2^2_R})} \tag{3.6}$$

5. Calculate the impulse weight for each neighborhood

$$w_I(x) = e^{(-\frac{ROAD(x)^2}{2^2_I})} \tag{3.7}$$

6. Calculate the joint impulsivity 'j' for each neighborhood

$$J(x, y) = 1 - e^{(-\frac{(\frac{ROAD(x)+ROAD(y)}{2})^2}{2^2_J})} \tag{3.8}$$

7. Compute the weighting function 'w' for each neighborhood

$$w_{x,y} = w_S(x, y) w_R(x, y)^{1-J(x,y)} w_I(y)^{J(x,y)} \tag{3.9}$$

8. Replace the central pixel value with the corrected pixel value according to the filter formula

Chapter 4

Conclusions

This work primarily focuses on comparing the efficiency of noise removal algorithms. The work reported in this thesis is summarized in this chapter. Sec. 4.1 lists the pros and cons of the work. 4.2 provides some scope for further development.

4.1 Achievements and Limitations of the work

The Adaptive Impulse Detection Using Center-Weighted Median Filters is a typical median based filter which produces the corrected image with the sharpest edges of all the algorithms discussed in this work. The algorithm is simple to implement and quick to execute. The corrected image at higher impulse noise of p=20% does not have the noise completely removed. Another pass of the filter on the corrected image will prove useful in achieving better results.

A New Impulse Detector for Switching Median Filters produces relatively more blurred images. But there are no distinct spots of impulse values in the corrected image even at higher values of p, e.g. at p=20% unlike the previous algorithm which preserves the sharpness but images appear spotted for higher values of p.

The Efficient Filtering Of Image Data Corrupted by Impulse noise algorithm serves true to its purpose and calculates the restored pixel values fastest of all the algorithms discussed here. The corrected image appears to be peppered with low impulse values. Although the images produced preserve the sharpness of edges better than the previous algorithm, the appearance of lower impulse values increase with increasing p, e.g. at p=20%.

The Impulsive Noise Removal Using Threshold Boolean filter produces subjectively the poorest results. The images are blurred, containing lines of impulse noise values. The algorithm has high space complexity and takes the longest to execute. The Universal Noise Removal Algorithm with an Impulse Detector tackles both Gaussian and Boolean noises. The corrected images produced by this algorithm are blurred the most among all other algorithms implemented.

4.2 Further Development

All the algorithms discussed above either blur the edges or do not efficiently remove the noise. We can try to implement and/or modify the existing algorithm so that they can smooth the distinct regions of the image without blurring the edges and improve their space and time complexities by implementing them more efficiently.

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